Global Brand Perception based on Social Prestige, Credibility and Social Responsibility: A Clustering Approach

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Abstract. Towards the merchandising of a global brand, it is necessary to establish guidelines for marketing managers to define appropriate standardization/adaptation measures. Therefore, it is required to understand the construct of susceptibility to global consumer culture (SGCC) to position the brand according to the wishes and preferences of consumers belonging to specific segments of the global market. Based on three dimensions of the SGCI, proposed in literature: (i) social prestige; (ii) brand credibility; and (iii) social responsibility. This study aims to identify groups of global consumers; from dierent cultural backgrounds, ages, countries, among other characteristics; who share similar interests. For this purpose, an analysis and a comparison of four clustering algorithms are proposed. Besides, the best number of groups for each algorithm is calculated to find the groups that best explain the behavior of the global consumer. The results confirm the existence of a hybrid culture of global consumption, which produces companies to segment consumers from different countries based on similar or shared needs.

Keywords: Global brands · clustering · social prestige · brand credibility · social responsibility · market segmentation.

1 Introduction

Global brands have several definitions among the literature, in this work, a combination of them was adopted: "are brands that are sold, marketed and widely recognized under the same name in multiple countries with generally standardized and centrally coordinated marketing strategies." [21, 29, 9]. In emerging countries, global brands are perceived as a kind of passport to global citizenship [17, 28]. Hence, global brands can express customers global identity; that is, consumers start to be considered part of the global consumer culture (GCC) [10].

At the same time, the concept of susceptibility to GCC (SGCC) emerged, as "a desire or a tendency for the acquisition and use of global brands" with conformity to consumption trend, quality perception and social prestige serving as antecedents [34].

Given this context, Hernani et al. [14] proposed a model that represents a global brand, which is related to the intention to purchase global brands as a result of susceptibility and can differ from one consumer to another according to their culture. Consequently, this model can describe how a particular segment of global consumption perceives global consumption trends. It integrated the measures of SGCC with seven dimensions: (*i*) conformity to consumption trends; (*ii*) quality perception; (*iii*) social prestige; (*iv*) social responsibility; (*v*) brand credibility; (*vi*) perceived risk; and (*vii*) information costs saved. In order to know the behavior profiles of global brands consumers, some works using clustering algorithms have been proposed. Their methodology is based on gathering descriptive attributes of the customers to divide them into groups with similar behaviour related to a product under consideration [18].

Following this idea, in this paper, it is proposed an approach to analyse and discover the consumer behaviour and susceptibility to the consumption of global brands in different cultural settings, based on three dimensions of the model mentioned above. Social prestige reflected in consumer attributions of social status and self-esteem through the consumption of global brands. Also, it can indicate a high status for a product associated with that particular brand [10]. Consumers tend to perceive the consumption of a prestigious brand as an indicator of social status, self-esteem, wealth or power [14]. Brand credibility that refers to how credible the information about a branded product is. It resembles the respectability of the brand according to the customer based on its: reliability, expertise, honesty, attractiveness, trust-spreading, and what is advertised by the manufacturer [20]. Therefore, the content clarity and credibility of a brand might rise the product value, reduce material expenses, and perceived risk to the users; consequently, increasing the consumers buying intention [27]. Also, social responsibility that includes consumer perceptions of the social responsibility of the global brand. This concept was introduced by Bodur et al. to differentiate social responsibility efforts at corporate and product brand levels [11]. A favourable social responsibility image reflects brand associations that tend to have a positive effect on consumer attitudes [13]. Hence, a suitable social responsibility marketing strategy can produce significant results because it builds confidence in consumers.

In the search for market segments that identify with global consumption trends, the marketing literature highlights the importance of the use of cluster analysis [23] because this method helps to identify and define market segments that are at the center of the marketing strategy of multinationals [31]. This methodological approach is not commonly used in seeking to understand consumer behavior due to its operative complexity. In this way, the contribution of this paper, seeks to obtain the profiles of consumers (from different cultural backgrounds, ages, countries, among other characteristics) and their perception of global brands (according to the metrics of susceptibility to the global consumer culture). Thus, four clustering algorithms are analyzed and compared, looking for the best number of clusters for each algorithm and comparing the groups of the algorithms, looking for the clusters that best explain consumer behavior. In this way, the interpretation of the clusters is carried out concerning their impact on the commercialization of global brands.

This work is organized into five sections. Section 2 briefly describes the data set and the cluster algorithms. Section 3, presents the experimental results and discussion and Section 4, report the conclusions and future work.

2 Methods

In this section, we concisely recall the main aspects regarding the dataset and the cluster algorithms applied to this analysis, including a suitable parameter selection for each algorithm.

2.1 Dataset

As described in [14], the data was acquired through a questionnaire sent via email to United States, Brazil, Peru, France and the Czech Republic undergraduate students of business degrees (economics, administration and accounting) and MBA students. It is worth mentioning that after removing duplicate and incomplete questionnaires, the final sample is composed of 412 questionnaires, distributed as shown in Figure 1. The ability scores of each of the seven dimensions of SGCC were estimated by applying the Item Response Theory (IRT). It should be noted that the ability score is normally expressed on a scale with an average of 0, standard deviation 1 and range of values between -3 and 3; which is a normalized score.

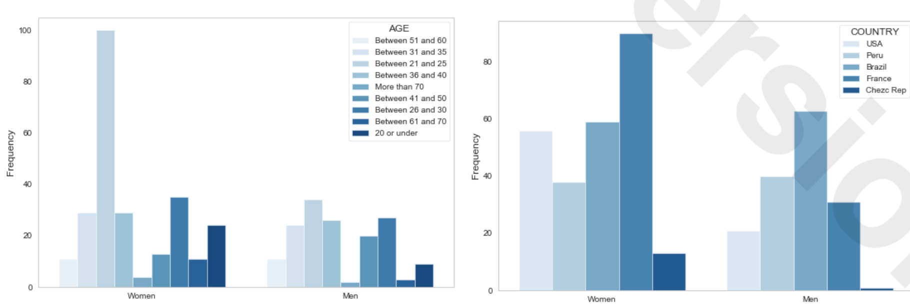

Fig. 1. Questionnaire participant's sex distribution according to age and country.

The variables considered from the model proposed in [14], are: (*i*) social responsibility; (*ii*) social prestige; and (*iii*) brand credibility. Once clusters have been founded, they need to be profiled using additional variables of interest, such as socio-demographic variables and behavioural variable [7]. In this case, we use age and gender; additionally, to incorporate the global consumer culture into the analysis, the consumers country was introduced.

2.2 Cluster Theory

Clustering is a method of unsupervised learning commonly used in many fields for statistical data analysis with the aim of grouping objects into classes of similar objects based on their locality and connectivity within an n-dimensional space [19] [33]. Clustering algorithms partition data into a certain number of clusters (groups, subsets, or categories).

Mathematically given a set of input patterns $\mathbf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_j, \ldots, \mathbf{x}_N\}$ where $\mathbf{x}_j = (x_{j1}, x_{j2}, \ldots, x_{jd})^T \in \Re^d$ and each measure x_{ji} is said to be a feature (attribute, dimension, or variable).

A (Hard) partitioning clustering attempts to seek a K partition of $\mathbf{X}, C = \{C_1, \ldots, C_K\}$ $(K \leq N)$, such that:

$$C_i \neq \phi, \; i = 1, \ldots, K; \tag{1}$$

$$\bigcup_{i=1}^{K} C_i = \mathbf{X}; \tag{2}$$

$$C_i \cap C_j = \phi, i, j = 1, \ldots, K \text{ and } i \neq j. \tag{3}$$

where N is the finite cardinality of the available representative data set and C_i is the total number of class types. For hard partitioning clustering, each pattern only belongs to one cluster. However, a pattern may also be allowed to belong to all clusters with a degree of membership, $u_{i,j} \in [0, 1]$, which represents the membership coefficient of the jth object in the ith cluster and satisfies the following two constraints:

$$\sum_{i=1}^{c} u_{i,j} = 1, \quad \forall j \quad \text{and} \quad \sum_{j=1}^{N} u_{i,j} < N, \quad \forall i \tag{4}$$

that is used in fuzzy clustering (see [15] and [25]).

For instance, it can be used to identify consumer segments, or competitive sets of products, or groups of assets whose prices co-move, or for geo-demographic segmentation. Therefore, its goal in marketing is to accurately segment customers in order to achieve more effective customer marketing via personalization. In this work, we chose four algorithms based on different ways of partitioning the space, described in Table 1.

Table 1. List of the four well-known algorithms chose in our work, including a brief description based on [32] [25].

Algorithm	Based on	Description
K-Means	Partition	The main idea is to update the center of the cluster which is represented by the center of data points, by iterative computation. The iterative process will be continued until some criteria for convergence (sum of squared Euclidean distances minimization) is met.
Gaussian Mixture Models	Distribution	GMM consists of several Gaussian distributions from which the original data is generated. Then, the data obeying the same independent Gaussian distribution, is considered to belong to the same cluster. This algorithm employs an iterative scheme, where in each step, the likelihood is increased, ensuring that the algorithm usually converges.
Fuzzy C-Means	Fuzzy Theory	The basic idea is that the discrete value of belonging label, $\{0, 1\}$, is changed into the continuous interval $[0, 1]$, in order to describe the belonging relationship among objects more reasonably. Then, FCM gets the membership of each data point to every cluster by optimizing an objective function.
Kohonen Network	Neural Network Learning	The core idea is to build a mapping of dimension reduction from the input space of high dimension to output space of low dimension on the assumption that there exists topology in the input data [8] [30].

3 Results and Discussion

In order to describe the results obtained from the clustering analysis, it is required first to select the best number of clusters to be used on each algorithm. Then, use the best model to visualize the consumer's segmentation, and finally, describe and discuss the clusters found and compare the algorithms results.

3.1 Selection of the Best Parameters and Number of Clusters

Determining the number of clusters is a challenging task when dealing with clustering algorithms. Besides, some algorithms have some additional parameters to be set in order to find the best model. Thus, we performed a grid search over the parameters listed in Table 2 (*Parameters*) optimizing the measure detailed in Table 2 (*Measure*). It is worth mentioning that we use a Python (scikit-learn) implementation to conduct our experiments.

For the K-Means algorithm, we use the Elbow method to find the best number of clusters. The Elbow method is based on the visualization of the value of a clustering criterion against the number of clusters ($n\_clusters$). As we keep increasing $n\_clusters$, there will be a decrease in the cost function. Then, a discontinuity in slope should correspond to the correct number of "natural"

Table 2. Clustering algorithm's parameters according to Python functions.

Algorithm	Function Name	Parameters	Measure
K-Means	KMeans (sklearn.cluster) [22]	n_clusters	sum of squared distances
Gaussian Mixture Models	GaussianMixture (sklearn-mixture) [22]	n_components covariance_type	bayesian information criterion
Fuzzy C-Means	fuzz.cluster.cmeans (scikit-fuzzy) [24]	n_clusters exponent_membership_function	fuzzy partition coefficient
Kohonen Network	neurolab.net.newc (NeuroLab [1])	[input_neurons, min_max_values] output_neurons	mean absolute error

clusters [12]. As can be seen in Figure 2, the optimal number of clusters using K-Means is two.

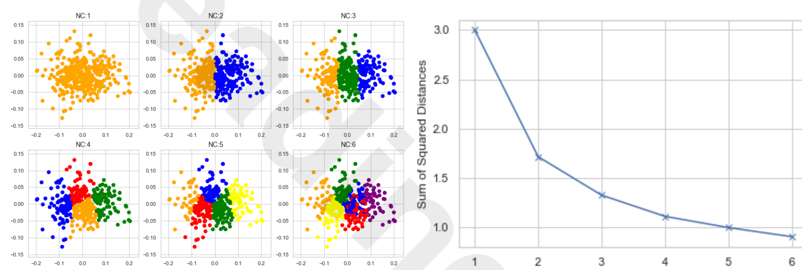

Fig. 2. Selection of the best number of clusters according to the Elbow method based on the sum of squared distances.

In order to find the best clustering model using Gaussian Mixture models, we performed a grid search using the number of clusters and the covariance matrix type, optimizing the Bayesian Information Criterion [26]. This criterion is used for model selection among a finite set of models where the model with the lowest BIC is preferred because it implies a better fit. According to Figure 3, the best model uses a diagonal matrix and two clusters.

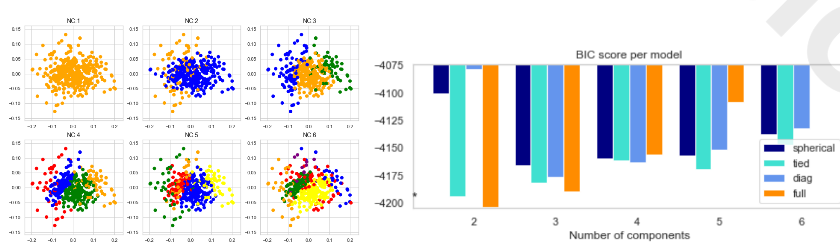

Fig. 3. Selection of the best number of clusters according to the lowest BIC measure using a diagonal covariance matrix.

The best model using the Fuzzy C-Means algorithm was found by performing a grid search over the number of clusters and the exponent of the membership function parameters; optimizing the Fuzzy Partition Coefficient (FPC) [4]. This coefficient is a metric which tells us how cleanly a particular model describes the data by measuring the amount of overlap between fuzzy clusters. It is defined on the range from 0 to 1, with one being best. Based on Figure 4, the best model achieved a FPC of 0.7 using two clusters.

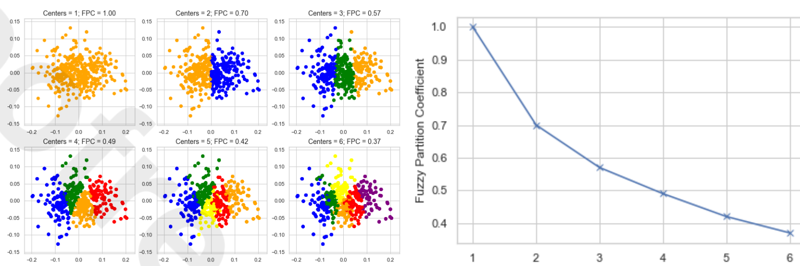

Fig. 4. Selection of the best number of clusters based on the highest Fuzzy Partition Coefficient, using two as the exponent of the membership function.

Regarding the parameters of the Kohonen Network, we trained it with two output neurons, as it was the best number of clusters found among the clustering algorithms described before. As can be seen in Figure 5, it minimizes the mean absolute error in a small number of iterations, mapping the dataset into two clusters, each center is highlighted in orange color.

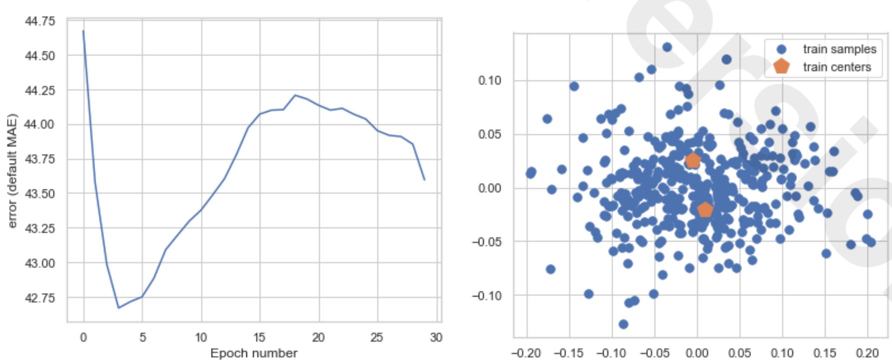

Fig. 5. Kohonen network training and the final position of the centers for each cluster.

3.2 Cluster Validation Measures

An essential step in the segmentation process is to evaluate the partitioning quality to test the validity of the algorithm [18]. According to literature, the evaluation measures can be categorized into internal and external indices. Most of them take into consideration the compactness of the objects in the same cluster and their separation in the distinct clusters [32]. In our experiments, we expressed the quality of the resulting clustering through two validity indices:

- Calinki-Harabasz, it is a "variance ratio criterion" giving some insight into the structure of the points[5]. The higher score relates to a model with better-defined clusters.
- Davies-Bouldin, it indicates the similarity of clusters which are assumed to have a data density which is a decreasing function of distance from a vector characteristic of the cluster [6]. A lower index relates to a model with better separation between the clusters.

As can be seen in Figure 6, the algorithm which obtained the best validation measures, is the Fuzzy C-Means. In the following section, it is detailed the interpretation of the clusters resulting from each clustering algorithm according to global brands marketing.

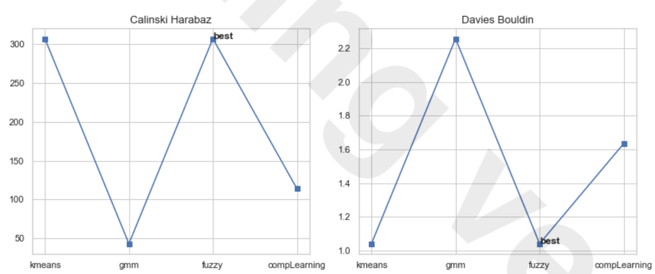

Fig. 6. Comparison of the validation indices obtained for the best number of clusters of each algorithm.

3.3 Results Interpretation from each Clustering Algorithm

K-Means: From the results depicted in Fig. 7(first row), it can be seen that this algorithm divides the dataset into two same-size clusters (206 for each group). As detailed in Table 3, $C1$ has a majority presence of women and men participants from Peru and the United States, between 31 and 40 years old whereas that $C2$ includes both sex participants from Brazil, France and the Czech Republic between 21 to 30 years. It shows a marked age difference between both groups, where $C2$ represents the younger consumers and $C1$ the older ones. Regarding the dimensions analyzed, when comparing Social Responsibility from the resulting clusters, it can be seen that both groups tend to be critical to the companies practices regarding this dimension. However, $C1$ tends to accept the social responsibility practices of global brands unquestioningly. Additionally, we can see that younger people are the ones who claim for a better role of global companies in the well-being of society. Concerning the Social Prestige, $C2$ is more reluctant to accept that global brands transmit prestige, due to its lowest ability score is -2.78 when compared to $C1$, which value is -1.46. Thus, older consumers tend to buy global brands in order to improve their self-image. Meanwhile, about Brand Credibility, $C1$ perceives a global brand as believable in contrast with $C2$, where they usually question the information provided by global brand companies. To summarize, we can conclude that younger consumers ($C2$) are more concern about the social responsibility of the global brand companies which leads to a high/low brand credibility, rising/reducing the sales according to their positive/negative perception; because as they do not perceive global brands as a symbol of social prestige they can do without them.

Table 3. K-Means Algorithm: Ability scores, demographic and genre distribution based on the clusters found.

Cluster	Country	Sex	SR	SP	BC
C1	**USA (63.64%)** **Peru (64.10%)** Brazil (49.10%) France (34.71%) Czech Rep (35.71%)	Women and Men $[31-40]$	$[-1.75, 2.71]$	$[-1.46, 2.62]$	$[-0.83, 2.28]$
C2	USA (36.36%) Peru (35.90%) **Brazil (50.82%)** **France (65.29%)** **Czech Rep (64.29%)**	Women and Men $[21-30]$	$[-1.75, 0.88]$	$[-2.78, 1.42]$	$[-2.56, 1.38]$

Gaussian Mixture Models: From the second row of Figure 7, we can conclude that $C2$ is almost included into $C1$. Furthermore, $C1$ groups 339 consumers including women between 21 and 25 years; and men with $21-40$ years (See Fig. 4). It also is represented by consumers from Peru, France and the Czech Republic. Meanwhile, $C2$ (73 people) has 24.6% of the Brazilian consumers and 18.2% of the USA consumers. It is characterized by the presence of women from 26 to 40 years and men from under 20 to 40 years. Based on the three dimensions analyzed by the clustering algorithm, both groups are concern about the social responsibility of the global brand they are interested in buying. However, $C1$ is less agreeable that $C2$, since the high ability score for this dimension in 2.0 for $C1$ and 2.71 for $C2$. Likewise, according to the Social Prestige ability scores grouped by this algorithm, $C2$ perceive global brands as a sign of prestige. Besides, $C1$ is also less persuaded by global brands advertising.

Table 4. Gaussian Mixture Models (GMM): Ability scores, demographic and genre distribution based on the clusters found.

Cluster	Country	Sex	SR	SP	BC
C1	USA (81.82%) **Peru (84.62%)** Brazil (75.41%) **France (87.60%)** **Czech Rep (85.71%)**	Women $[21-35]$ Men $[21-40]$	$[-1.75, 2.0]$	$[-2.78, 2.17]$	$[-2.56, 2.28]$
C2	**USA (18.18%)** Peru (15.38%) **Brazil (24.59%)** France (12.40%) Czech Rep (14.29%)	Women $[26-40]$ Men $[<20-40]$	$[-1.75, 2.71]$	$[-1.67, 2.62]$	$[-0.83, 2.28]$

Fuzzy C-Means: As can be seen in Figure 7(third row), the clustering algorithm groups 204 consumers in $C1$ and 208 in $C2$, respectively. Besides, as can be seen carefully in the dimension histograms, they are the same as the K-Means histograms. Moreover, comparing the ability scores from Tables 5 and 3, both clustering results share the same values. However, they differ in the age ranges, $C1$ (26-40 years) and $C2$ (21-25 years) consumers are younger than K-Means clusters, but they keep their perception towards the global brands. $C2$ consumers can increase their susceptibility to acquiring a global brand product according to positive brand credibility and social responsibility activities. Meanwhile, $C1$ consumers tend to buy global brands as a sign of their social prestige.

Table 5. Fuzzy C-Means: Ability scores, demographic and genre distribution based on the clusters found.

Cluster	Country	Sex	SR	SP	BC
C1	**USA (62.34%)** **Peru (64.10%)** Brazil (49.18%) France (33.88%) Czech Rep (35.71%)	Women and Men $[26-40]$	$[-1.75, 2.71]$	$[-1.46, 2.62]$	$[-0.83, 2.28]$
C2	USA (37.66%) Peru (35.90%) **Brazil (50.82%)** **France (66.12%)** **Czech Rep (64.29%)**	Women and Men $[21-25]$	$[-1.75, 0.88]$	$[-2.78, 1.42]$	$[-2.56, 1.38]$

Kohonen Network: This algorithm grouped 220 consumers mostly from Brazil, France and the Czech Republic in $C1$; including women from under 20 to 50 years, and men between 21-30 years (See Table 6). In $C2$ there is a total of 192 consumers from the United States and Peru, grouped by women between 31-40 years and men between 36-60 years. According to the Social Responsibility dimension, $C1$ and $C2$ shared the lowest limit of the ability score (-1.75), which means that perceived this dimension as relevant before acquiring a global brand. However, $C2$ seems a little more persuadable when the company is not socially responsible. Moreover, the $C1$ represents consumers that buy global brands in order to achieve some social prestige level. Regarding the brand credibility, both clusters present the same upper limit (2.28); however, the $C2$ tends to trust more in what the brand offers to them.

Table 6. Kohonen Network: Ability scores, demographic and genre distribution based on the clusters found.

Cluster	Country	Sex	SR	SP	BC
C1	USA (42.86%) Peru (48.72%) **Brazil (56.56%)** **France (59.50%)** **Czech Rep (57.14%)**	Women $[< 20 - 50]$ Men $[21 - 30]$	$[-1.75, 2.71]$	$[-2.78, 0.61]$	$[-2.56, 2.28]$
C2	**USA (57.14%)** **Peru (51.28%)** Brazil (43.44%) France (40.50%) Czech Rep (42.86%)	Women $[31 - 40]$ Men $[36 - 60]$	$[-1.75, 2.51]$	$[-0.49, 2.62]$	$[-2.26, 2.28]$

4 Conclusions

This study aims to identify groups of global consumers who share similar behaviors based on three characteristics of the SCCG (social prestige, brand credibility and social responsibility). In order to achieve this goal, we analyze and compare four clustering algorithms, which allows obtaining the best number of groups for each algorithm and compare its solutions, to finally discover the best groups that explain the behavior of the global consumer. From the results, we can conclude that three clustering algorithms converged with the marketing theory (Kmeans, Fuzzy C-means and Competitive Learning). However, the Gaussian Mixture Model (GMM) algorithm does not reflect what is stated in the marketing literature.

As can be seen in the interpretation of the results, the three algorithms converge with the literature. The clustering takes place across the countries, separating the consumers into two groups: the youngest consumers (Brazilian, French and Czech); and the consumers of mature age (Americans and Peruvians).

Fig. 7. Different algorithms cluster's visualization: The first column shows a 3D visualization of the clustering results, where cluster 1 is highlighted in green and Cluster 2 in red color, respectively. The second column depicts the histogram of the three variables of interest, part of the clustering analysis; where cluster 1 is highlighted in yellow and Cluster 2 in blue color.

This separation is justified by the conclusions of [2] and [16], where they conclude that businesses that operate at a global level should group target across different countries if they share similar preferences and needs. Therefore, it confirms the existence of a hybrid culture of global consumption [2].

Besides, in [2], the authors comment that the culture of global consumption represents a collection of common signs (e.g. products such as blue jeans and brands like iPod), which is understood and accepted by certain market segments, such as young people around the world. This situation is part of the obtained clustering results from three algorithms (K-means, Fuzzy C-means and Competitive Learning) which are valid in the literature because the ability scores for the analyzed dimensions for Brazilians, French and Czechs, tend to be more towards to the negative than to the positive. This circumstance denotes a greater acceptance by the proposals of global brands; unlike the Americans and Peruvians who show less acceptance and some questioning about the perceptions of the global brands. Our findings suggest that consumers in different countries develop common beliefs about global citizenship. It is a fact that consumers in favor of global brands are often younger [3]. Therefore, it is necessary to increase the intention to purchase global brands across groups that share perceptions on the characteristics of SGCC. Consequently, if the companies adopt the components of their branding programs according to the market and create conditions for each cluster identified of consumers; they could increase their benefits, for instance, cost savings.

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